Multi-resolution time series imagery for forest disturbance and regrowth monitoring in Queensland, Australia

Schmidt, Michael; Lucas, Richard; Bunting, Peter; Verbesselt, Jan; Armston, John

Published in:
Remote Sensing of Environment

DOI:
10.1016/j.rse.2014.11.015

Publication date:
2015

Citation for published version (APA):
Schmidt, M., Lucas, R., Bunting, P., Verbesselt, J., & Armston, J. (2015). Multi-resolution time series imagery for forest disturbance and regrowth monitoring in Queensland, Australia. *Remote Sensing of Environment*, *158*, 156-168. https://doi.org/10.1016/j.rse.2014.11.015

Multi-resolution time series imagery for forest disturbance and regrowth monitoring in Queensland, Australia

Michael Schmidt[1,2], Richard Lucas[3], Peter Bunting[4], Jan Verbesselt[5], John Armston[1,2]

1 Remote Sensing Centre, Environment and Resource Sciences, Department of Science, Information Technology, Innovation and the Arts, GPO Box 2454, Brisbane, Queensland 4001, Australia

2 Joint Remote Sensing Research Program, School of Geography, Planning and Environmental Management, The University of Queensland, Campbell Rd, Brisbane Queensland 4072, Australia

3 School of Biological, Earth and Environmental Sciences (BEES), the University of New South Wales (UNSW), High Street, Kensington, NSW 2052, Australia.

4 Institute of Geography and Earth Sciences, the University of Wales, Aberystwyth, Ceredigion, SY23 3DB, United Kingdom

5 Laboratory of Geo-information Science and Remote Sensing, Wangeningen University, Droevendaalsesteeg 3, 6708PB Wageningen, Netherlands

Abstract

High spatio-temporal resolution optical remote sensing data provide unprecedented opportunities to monitor and detect forest disturbance and loss. To demonstrate this potential, a 12-year time series (2000 to 2011) with an 8-day interval of a 30 m spatial resolution data was generated by the use of the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) with Landsat sensor observations and Moderate Resolution Imaging Spectroradiometer (MODIS) data as input. The time series showed a close relationship over homogeneous forested and grassland sites, with r2 values of 0.99 between Landsat and the closest STARFM simulated data; and values of 0.84 and 0.94 between MODIS and STARFM. The time and magnitude of clearing and re-clearing events were estimated through a phenological breakpoint analysis, with 96.2 % of the estimated breakpoints of the clearing event and 83.6 % of the re-clearing event being within 40 days of the true clearing. The study highlights the benefits of using these moderate resolution data for quantifying and understanding land cover change in open forest environments.

Keywords: STARFM, BFAST, Landsat TM/ETM+, MODIS, Forest change, clearing, time series, regrowth, data fusion

1. Introduction

Globally, forest loss and degradation is the second largest contributor to the post-industrial revolution increase in atmospheric carbon dioxide (CO_2; van der Werf, et al., 2009). Whilst much of the conversion from forest to non-forest (e.g., agriculture, urban areas, and infrastructure) over the past four decades has been observed using satellite sensor data, losses associated with degradation have been less discernable and consequently underestimated (Asner et al., 2005). Uncertainties also remain regarding the contribution to carbon emissions. Quantifying the extent and also magnitude of degradation is therefore important, particularly given that affected areas often do not recover or are eventually cleared.

Many studies investigating ways to map forest disturbance have focused on changes in the biophysical properties of forests, with these determined largely through the use of spectral data or derived indices such as the Normalised Difference Vegetation Index (NDVI; Tucker, 1979). For this purpose, and primarily because of the high temporal (near daily) coverage, coarse (~1 km) spatial resolution Advanced Very High Resolution Radiometer (AVHRR) and SPOT-VEGETATION or Terra-1 Moderate Resolution Imaging Spectrometer (MODIS; 1 km to 250 m) have been used (Running and Nemani 1988; Schöttker, et al. 2010; Verstraete and Pinty 1996). In particular, these data allow for the detection of a) seasonal change (e.g. phenological behaviour influenced by temperature and rainfall pattern), b) gradual change (e.g. impacts of long term climatic or land management changes) and c) abrupt changes and disturbances (e.g. land clearing or fire), as shown by Verbesselt et al. (2010). Finer (~ 30 m) spatial resolution data from the Landsat sensors have allowed detection of specific events, such as vegetation clearing, selective logging or fires (Kennedy, et al. 2009). These data have not though been widely used for process monitoring because of the low temporal frequency (16 days for Landsat), which has been reduced further by cloud cover, adverse atmospheric conditions and sensor problems (Baumann, et al. 2011; Kennedy, et al. 2009). However, the release of the Landsat archive at no cost (Wulder et al., 2012) has provided new opportunities for assessing historical changes in landscapes.

To provide the option of high spatial resolution and high temporal frequency, a number of data fusion techniques have been developed that link MODIS and Landsat sensor data (e.g., Gao et al., 2006; Roy et al., 2008; Zhu et al., 2010). Of note is the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM), which has been applied successfully for a range of studies and purposes (Gao, et al. 2006; Hilker, et al. 2009a; Watts, et al. 2011). For example, Walker et al. (2012) demonstrated the usefulness of the STARFM algorithm for phenological studies in the drylands of Arizona by using 12 STARFM predicted images. Schmidt et al. (2012) used STARFM to predict 333 Landsat sensor images over a 7.5 year time period, with these then used to study regional ecological and phenological processes in a heterogeneous Northern Australian savanna. ESTARFM (Zhu, et al. 2010) and mESTARFM (Fu, et al. 2013) have been successfully applied as an improvement on STARFM, although findings of Emelyanova et al (2013) are inconclusive in establishing whether this improvement is evident for all environments (e.g., with a dominant temporal variance, STARFM gave a superior performance). Hence, the less complex STARFM algorithm was applied here. Hilker et al. (2009b) used a STARFM-based fusion model (STAARCH) for mapping forest disturbances. This algorithm computes a Disturbance Index (DI) based on a Tasselled Cap (Kauth & Thomas, 1976) transformation and NDVI data for each simulated image. A regionally adapted mask of mature forest is then used to scale and empirically threshold the DI time series. The pixel neighbourhood is included to reduce DI noise.

An environment where the STARFM algorithm has not been evaluated is the open forests and woodlands of northern Australia (Williams et al., 1997; Schmidt, et al. 2012, Bhandari, et al. 2012). Nevertheless, temporal comparisons of Landsat imagery have been undertaken to allow detection of forest loss. In particular, the Queensland Department of Science Innovation Technology and the Arts (DSITIA) developed a program to monitor vegetation change using Landsat data; the Statewide Landcover and Trees Study (SLATS). In this programme, annual state-wide maps of Foliage Projected Cover (FPC) have been generated using empirical relationships between ground-based estimates from a range of vegetation types and both Landsat data and climate variables (Armston, et al. 2009, Danaher et al, 2010). From these data, forest losses have been reported annually since 1999 and over longer time intervals between 1988 and 1999 (Danaher et al, 2010). The scale of the Landsat scale imagery has also proved adequate for describing the complex and spatially heterogeneous landscapes occurring across the state (Danaher, et al. 2010). In this case, images captured during Queensland's dry season are preferentially selected, as these give best differentiation between the dry ground cover layer and the non-deciduous woody vegetation.

To evaluate the potential application of the STARFM algorithm for determining undisturbed forest phenology and detecting and spatially differentiating the date and magnitude of forest change, a 12-year time series (2000 to 2011; with an 8-day interval) of Landsat and STARFM simulated images was used. The study was conducted in the Injune Landscape Collaborative Project (ILCP) research area west of Injune in central southeast Queensland. A major benefit of using this area was that large scale (< 1:4000) true colour aerial photography and Light Detection and Ranging (LiDAR) data were acquired in 2000 and 2009 over a well-defined grid of 150 500 m x 150 m Primary Sampling Units (PSUs), with 4 km between each in the north-south and east-west directions. Hence, these data could be used to establish reference sites that had experienced limited change as well as disturbance and regeneration at the stand level over the period of the time-series. The study sought to establish whether a) a baseline of vegetation phenology over the 12 year period could be described for undisturbed natural vegetation based on the NDVI, b) time-series analysis could be used to indicate the timing and magnitude of disturbance events, and c) an increasing trend in NDVI metrics (e.g., dry season minima) could be associated with the regeneration of forests.

2. Study area

The study focused on the ILCP research area, which is located approximately 100 km west of the township of Injune in central southeast Queensland (Figure 1a, b). The landscape can be described as a southern savanna region characterised as having variable rainfall and an ecosystem that is generally water limited. The majority of the landscape consists of forests and agricultural lands, with some abandoned to regrowth. Scattered buildings (primarily farmhouses) and unsealed roads are the main urban infrastructures occurring. The 37 x 60 km area was selected for the initial study as extensive tracts of vegetation were being cleared in the late 1990s and the open forests and woodlands (wooded savannas) contained structural formations typical to many occurring in Queensland. The study area was divided into a large sample grid of 150 (10 columns x 15 rows) Primary Photo Plots (PPPs; Figure 1c) over which large-scale 1:4000 aerial photographs were acquired in 2000. Within these, 500 m x 150 m PSUs (Figure 1d) were located in the stereo overlap. Each PSU was further divided into 30 secondary sampling units (SSU) of 50 m x 50 m. The original study area was chosen to be at the centre of the Landsat satellite swath (Tickle, et al. 2006), but was extended south by 20 km to include areas where a range of land clearing activities were occurring.

Between 2000 and 2011, changes in the structure, biomass and species composition of forests occurred within the study area. Changes were caused by natural events such as fires, and human activities including stock grazing, selective and complete tree clearing by landholders (primarily for agricultural purposes) (Goodwin and Collett, 2014). Changes in climatic conditions (e.g., drought and flooding) also impacted on the structure and composition of forests. For example, in 2006, many large and mature rough barked apple (Angophora floribunda) trees died as a consequence of a prolonged period of drought, but smooth barked apples (A. leiocarpa) were unaffected (Lucas, et al. 2008). Regrowth following clearing for agriculture or fires was also commonplace.

FIGURE 1 near here, please.

3. Data and methods

3.1 Spaceborne, airborne and field data

For the ILCP study area, 97 Landsat sensor data with a cloud cover of less than 20 %, acquired from December 1999 to September 2011 were obtained, with 69 and 28 acquired by the Landsat Thematic Mapper (TM) and Enhanced TM (ETM+) respectively (Table 1a). The Scan Line Corrector (SLC)-off effect (which results in missing data in alternate groups of lines at the edge of the image) was evident within 11 ETM+ scenes (Pringle et al. 2009). For the same period, 525 MODIS images were available from which the MODIS Bidirectional Reflectance

Distribution Function (BRDF) model parameters (MCDS43A1) and the BRDF/Albedo quality product (MCD43A2) had been derived. The latter is a quasi-roll-on version of the 16-day MODIS composites and is produced every 8 days (Roy et al., 2008).

TABLE 1 near here, please.

Across the PSU grid, discrete return LiDAR (using an OPTECH ALTM1020) and 1:4000 scale colour aerial photographs had been acquired in 2000, with a repeat coverage colour aerial photographs and full waveform (RIEGL LMS-Q560) LiDAR obtained in 2009. Flight height and pulse densities were 150 m and 1 pulse per m2 in 2000 and 400 m and 4 pulses per m2 in 2009. Both LiDAR datasets were processed to a 1 m spacing. These data were used to obtain estimates of height and cover for each PSU for the years 2000 and 2009 based on the methods outlined in Tickle et al. (2006). A comparison of these data allowed areas that had remained undisturbed or otherwise to be identified. Through interpretation of the 2000 aerial photography, forest types were delineated and assigned with a community code, with these representing the primary dominant, co-dominant and/or sub-dominant tree species or genera. The interpretation of these data was assisted by forest inventory data collected in 2000 from selected (34) 50 m x 50 m SSUs located within the PSU grid (Tickle et al., 2006), with this including measures of vegetation structure (cover, height and diameter distributions) and species type. More limited field campaigns were conducted in July 2006 (to collect information on species composition from a range of SSUs) and April 2009 (during which forest inventory data were collected from 6 SSUs that had been inventoried in 2000 and from additional sites within selected SSUs).

3.2 Data pre-processing

To guarantee the radiometric consistency of the Landsat sensor data, the algorithm outlined by Flood et al. (2013) to derive standardised surface reflectance for Landsat TM and ETM+ imagery was applied and BRDF-adjusted reflectances were then calculated based on a solar-zenith angle of 45o. All Landsat sensor data were screened for cloud and cloud shadow using an automated masking approach (Zhu and Woodcock, 2012) with manual refinement. MODIS BRDF-adjusted reflectances, also with a solar zenith angle of 45o, were derived using the Ross-Thick Li-Sparse reciprocal BRDF model and the parameters derived from the MCD43A1 model. The MODIS quality product (MCD43A2) was applied rigorously such that only those pixels associated with a 'good' or 'very good' BRDF inversion were used in subsequent analyses.

3.3 Generation of time series datasets

For each date of MODIS image acquisition, a prediction of reflectance at moderate spatial resolution was made using the STARFM algorithm (Gao et al., 2006). The STARFM algorithm simulates pixel values based on spatial weights determined by regional statistics between spectrally similar medium resolution Landsat and coarse resolution MODIS image pairs. Changes in reflectance in the coarse resolution MODIS images are applied to the fine resolution Landsat image. The algorithm produces a synthetic image from base pairs of Landsat and MODIS images at the time t0 and a MODIS image at the prediction time tk. STARFM was run in the mode of using two base pairs at t0 and tk+x. By applying the algorithm over the period 2000-2011, an 8-day temporal series of moderate (i.e, 30 m) spatial resolution BRDF adjusted reflectance data was generated (Table 1b). The Landsat 7 ETM+ data were for the time period

December 1999 to May 2003 but, thereafter, Landsat 5 TM data were used in preference as data line drop outs associated with the SLC-off effect reduced the reliability of predictions using the STARFM algorithm. To avoid spatial data gaps, no two consecutive Landsat 7 ETM+ images with the SLC-off effect were used (Figure 2).

FIGURE 2 near here, please.

NDVI time series data of the simulated dataset and MODIS were compared to the Landsat sensor data acquired. To confirm the consistency of the time series datasets for different ecological situations, NDVI trajectories for two homogeneous regions at the MODIS scale were calculated and compared. The regions were a 1.5 km x 1.5 km forested area (R1) and a 1 km x 1 km formerly cleared (between 1988 and 1997) grassland area (R2; identified in Figure 3b). The time series of NDVI was smoothed using the Savitzky-Golay filter with a length of 5 to reduce noise but still expose abrupt change events that might occur in the series (Jönsson and Eklundh, 2004). Figure 3 (a-c) depicts the spatial details of a Landsat 5 image (a) and MODIS image (b) used to simulate a STARFM image (c) for the date of the MODIS image. Figure 3(d) displays spatially the SLATS clearing eras. A reference grid showing the PSUs is also overlain (Figure 3a).

FIGURE 3 near here, please.

3.4 Establishing reference data

The floristic composition of the landscape was determined by summarising the occurrence of species within each of the 4500 SSUs, as determined from aerial photograph interpretation (Tickle, et al. 2006). Tickle et al. (2006) developed a system of three-letter symbols for species description in the region, which was adopted in this study. The major species in the region were Brigalow (Acacia harpophylla; BGL), Cyprus pine (Callitris glaucophylla; CP-), Poplar Box (Eucalyptus populnea; PBX), Rough-barked Apple (Angophora floribunda; RBA), Silver-leaved Ironbark (Eucalyptus melanaphloia; SLI), Smooth-barked Apple (Angophora leiocarpa; SBA), Sandalwood Box (Eremophila mitchellii; SWB), Tumbledown Gum (Eucalyptus dealbata; TDG), Gum-topped Box (Eucalyptus dura; GTI) and various Eucalyptus species (EUS). Approximately 70% of the dominant species were CP-, SLI, SBA and EUS. However, pure stands of particular species were rare, and these same species were also co- or sub-dominant. The most frequent associations (representing 31% of the total) were PBX and SWB communities (termed PBXSWB) and CP- and SLI or SBA with either dominating (i.e., CP-SLI, SLICP-, CP-SBA, SBACP-).

For each of the SSUs, estimates of maximum stand height (m) and cover (%) were generated from the LiDAR data acquired in 2000 and 2009 and using the algorithms outlined in Tickle et al. (2006) and Lee and Lucas (2007). SSUs that had experienced changes (or otherwise) were identified by comparing these LiDAR-derived products. SSUs associated with minimal change (i.e., < 20% of both median height and cover) were assumed to be comparatively ‘stable’. In each case, this was confirmed by referring to the aerial photography acquired in the same two years, with these being of sufficient spatial resolution to resolve individual tree crowns and the growth and loss of individual plants or clusters of vegetation. SSUs that had experienced more than a 20% change in height and cover were assigned to a change category (degradation, clearing or regrowth) with the causes and nature (i.e., natural or anthropogenic) of change events and processes (e.g., fire, clearing for agriculture, selective logging, grazing) also established through reference to the time series of aerial photography and other imagery available for the ILCP area. Where regeneration occurred between 2000 and 2009, the species composition of the regenerating forests was observed (in the field) to be different (in some cases) from that of the pre-cleared/degraded vegetation. Hence, a species code was unable to be assigned with confidence except in the case of BGL which was distinguishable in the 2009 aerial photography by its visual appearance (typically silver-blue in crown colouration) and spatial arrangement (a high density of individuals on previously cleared land).

3.5 Time series data analysis

NDVI time series values were extracted from the STARFM data and spatially averaged for each SSU. A time series break-point analysis was performed by applying the Breaks for Additive Seasonal and Trend (BFAST) algorithm (Verbesselt et al., 2010), with this used to establish where vegetation disturbance (e.g., through clearing for agriculture, logging or fire) occurred. The BFAST algorithm integrates an iterative decomposition of the additive components of trend (T), seasonality (S) and remainder components (noise; e), with abrupt, gradual, and seasonal change detected. Therefore, BFAST separates temporal variability from phenological change and performs a phenological change detection (Verbesselt et al., 2010). The model fits a piecewise linear trend and seasonal model and is of the form:

$$Yt = Tt + St + et \qquad \text{Equation (1)}$$

where the time-steps t range from 1 to n. Through this approach, the most significant change event in the time-series is located.

3.6 Temporal data validation

To validate the timing and magnitude of the clearing events, reference was made to the SLATS annual forest clearing data layers. These raster layers, which report clearing annually since 1999, were segmented into spatially coherent clusters, which were then assigned a time and magnitude of the clearing event as identified using BFAST (based on the most significant breakpoint in the time-series). The confidence interval around the clearing date was also assigned.

Further validation was performed using the full time-series, including imagery that were not used within the STARFM algorithm or supported variable amounts of cloud cover. Using these data, the clearing events that occurred were interpreted visually for each SSU that intersected the SLATS clearing layers. Each SSU was then associated with the last image date before clearing and the first thereafter. The same procedure was applied for areas of potential re-clearing. The confidence intervals around the breakpoint estimates of BFAST were compared and intersected with the "true" clearing interval to obtain a validation for the temporal clearing estimate.

3.7 Identification of vegetation regrowth

After a clearing event, an increase in the NDVI might be expected as foliage and canopy cover increases over time. To establish whether this occurred, the time series data were divided into annual cycles starting with the end of the dry season (determined as November 1st) to the onset of the wet season in the following year (October 31st). For each cycle, a dry season minimum NDVI map was generated, with this typically associated with the driest conditions where all remaining greenness in the deciduous savannah was attributable to woody vegetation (i.e., the non-grass layer). Trend lines in the minimum value of the NDVI for the duration of the time series were then used to establish trends in relation to forest growth.

4. Results

4.1 8-day STARFM generated data

The STARFM data generated from coarse spatial resolution MODIS and Landsat sensor data provided a similar representation of the spatial characteristics of the forest and agricultural elements within the landscape (Figure 3a-c). Comparisons of the red and near infrared reflectance recorded by the Landsat sensor (1st June 2004) and simulated using the STARFM algorithms also indicated a close correspondence (Figure 4); the Landsat image was not used in the STARFM data simulations.

FIGURE 4 near here, please.

In general, the time series behavior of the NDVI between the MODIS and the STARFM predictions showed a close correspondence (Figure 5) for the two test regions R1 and R2, with these representing the forest and grassland site respectively. In Figure 5, it is evident that a very different phenology and trend would be provided if Landsat sensor data alone were used (examples within the dotted lines). This is particularly the case regions with rainfall limited vegetation growth e.g. in savanna regions where vegetation phenology is driven by highly variable rainfall.

FIGURE 5 near here, please.

In some cases, NDVI values derived from the original Landsat data tended to be higher or lower during periods of seasonal minima or maxima respectively compared to MODIS NDVI values, particularly for the grassland site (e.g., in 2001). These differences were most likely due to the coarser spatial resolution of the MODIS data and the sampling procedure within the STARFM, which can result in removal of extreme values and alterations of averaged values at the Landsat scale. Some gaps were evident in the MODIS data (one for R1 and two for R2), which were identified as 'bad' values in the MODIS quality flag files. The correlations (r) between the MODIS and STARFM time series for Regions 1 and 2 were 0.92 and 0.96 respectively (r2 = 0.84 and 0.94), with root mean square error (RMSE) values of 0.026 and 0.031. The correlations between the Landsat and the closest STARFM simulated data were 0.996 for both the forested and grassland site (r2 of 0.992), with an RMSE of 0.006 and 0.011 respectively. The residuals of this comparison (NDVILandsat – NDVISTARFM) are shown in Figure 6; the closed STARFM image date closest to the respective Landsat scene was selected. It is noticeable that the RMSE is higher for Region 2 despite the correlation being similarly quite high with this attributable to the higher range of the NDVI.

FIGURE 6 near here, please.

A few outliers were observed with these being mainly associated with smoke plumes caused by bush-fires that were not included in the cloud masks.

4.2 Forest and land cover dynamics within the ILCP

Comparison of the LIDAR data from 2000 and 2009 indicated that 58% of PSUs experienced no significant changes in height or cover and were regarded as relatively stable over this period. These communities included those dominated or co-dominated by CP-, SLI, SBA, PBX, SWB, TDG or EUS (i.e., codes CP-SLI, CP-SBA, SLICP-, SBACP-, PBXSWB and PBXTDG and EUS); Table 2. Increases in both median height and cover of > 20% were evident within 12% of the PSUs, with losses occurring in 8%. Areas of regrowth were associated with PSUs where at least 20% of the contained SSUs showed more than a 20% increase in median height and cover. As an example, in PSU 108, an area of about 3 hectares experienced an increase of 2-6 m in height between 2000 and 2009, as determined through time series comparison of LiDAR data (Figure 7). Within the regrowth communities, PBX and BGL were dominant although in the former case, a greater mix of other species (e.g., SWB) occurred. Forests that were cleared between 2000 and 2009 included those dominated by PBX and co-dominated by CP- and SLI (CP-SLI; 1 SSU) whilst more areas had regenerated following extensive clearing in the period leading up to 2000 (Table 3). A further 12% had experienced some level of change (whether positive or negative) and 10% remained deforested through the period.

FIGURE 7 near here, please.

TABLE 2 near here, please.

4.3 NDVI Trajectories

4.3.1 Stable forests

For relatively stable forest areas, defined using the time-series of LIDAR data, differences in the magnitude of mean Landsat-derived FPC varied as a function of species mix (Table 4), ranging from 30.4 to 48.0; the deviation over the period 1999 to 2008 was, at most, 2.2 %. This indicated that the majority were in the open forest category. Furthermore, trends in NDVI were similar for the communities considered, with these mainly differing in magnitude, as illustrated in Figure 8a and b. The low points in the time series were associated with a comparative lack of rainfall.

TABLE 3 near here, please.

TABLE 4 near here, please.

Despite comparatively lower canopy cover (as reflected in the FPC values), the highest values in the NDVI were associated with forests co-dominated by TDG and SBA. The lowest trending NDVI was associated with communities co-dominated by CP- and SLI, with the needle-like leaves of the former being of low greenness despite a high FPC.

FIGURE 8 here, please.

In all cases, the NDVI rarely varied by more than 0.2 overall and no more than 0.1 from the mean value. Whilst the NDVI trends for PBXTDG and EUSCP- were without major deviation from the time series mean, those associated with SBACP- and CP-SBA exhibited some anomalies with deviations greater for CP-SBA in January-February in 2004, 2008 and particularly in 2010.

4.3.2 Clearing of forests

For disturbed vegetation, a rapid decrease in the NDVI was observed immediately following the disturbance event. Two examples are given in Figure 9 a) relative to the stable vegetation trajectory, where a clearing event occurred in PSU 108 in late 2000 in an area containing a mix of CP-, SLI and EUS (CP-SLIEUS), and PSU 68 in 2002 (dominated by PBX). Figure 9 b) and c) illustrate the automatic breakpoint detection in the STARFM-based NDVI time series. Estimates of the date of clearing as well as the confidence interval and the magnitude of the event are displayed graphically in Figure 9 b) and c). Prior to the clearing events, the mean temporal signature was similar to that of vegetation that had experienced minimal disturbance. After the event, the behaviour changed dramatically, initially following a trend more typical of grasslands (high NDVI amplitude and narrow low frequency). However, as the regrowth matured towards 2011, the signature became more similar to that of stable vegetation. The slopes of the fitted trend line after the clearing events were 0.015 for PSU 108 and 0.022 for PSU 68 (over ~10 year period). As a consequence of clearing forest vegetation, a drop in NDVI from 0.61 to 0.26 and from 0.44 to 0.28 was observed for these PSUs respectively. In both cases, the change event was detected with BFAST (Verbesselt, et al. 2010; Figure 8b and c) and was estimated to be 16th November 2000 and 29th August 2002 respectively.

FIGURE 9 near here, please.

4.3.3 Regenerating vegetation

In several areas, vegetation clearing occurred prior to the earliest date of the study period. The comparison of NDVI values for non-forest and forested areas, estimated for the date associated with the seasonal minima, indicated relative stability. However, the seasonal minimum NDVI for regrowth areas progressively increased for PSUs 68 and 108 (Figure 10). In most areas, regrowth was dominated by BGL or PBX mixed with other species (e.g., SWB, SLI) within the community.

FIGURE 10 near here, please.

4.5 Temporal validation

All clearing events could visually be identified to within a maximum of 60 days of any two consecutive Landsat acquisitions (using all available images). Figure 11 visualises the clearing and re-clearing data. The first date of the validation interval (i.e. before clearing) is plotted as base value (zero) and the other data points relative to this: clearing validation interval, the BFAST breakpoint estimate and confidence interval for each SSU. Clearing and re-clearing were evaluated separately in Figure 11a) and b).

The different width on the data population of the validation intervals and breakpoint confidence intervals is visible as are the events where the intervals are not intersecting (as difference in days).

FIGURE 11 near here, please.

The one large outlier (>200 days) in Figure 11b) could be identified as a gully that did not burn in a fire in September 2003 (like the other data points of this PSU) so that a later, non-clearing event was attributed as the event with the most significant change in BFAST.

The number of SSUs (%) where the breakpoint confidence interval intersected with the validation interval is show in Table 5, with this being 65.8% for clearing and 81.2 % for re-clearing. As the NDVI time series was filtered using a Savitzky-Golay filter, the analysis was repeated but increasing the confidence interval by one time step (8 days). In this case, 94.9% and 92.5 % of the intervals intersected for the clearing and re-clearing states respectively. This indicated that the majority of the clearing date was estimated as being close to the actual clearing event. In the case of a well-defined, sharper NDVI drop in the time series, the confidence interval was generally smaller (see also Figure 9). The confidence intervals for the primary clearing were substantially smaller than for the re-clearing events (Table 5).

TABLE 5 near here, please.

As a clearing event can be at either end of the validation interval (1st day after the interval start or the last day before the interval end), a “best case” and a “worst case” was calculated as a minimum and maximum time difference between the interval end points (validation interval and breakpoint confidence interval). The median of the minimum absolute difference between the intervals (best case) is 1 time step or 8 days; the maximum is 8 time-steps or 64 days. For the worst case, 96.2 % of the estimated breakpoints of the clearing event and 83.6 % of the re-clearing event were within 40 days of the true clearing (Table 6).

TABLE 6 near here, please

4.7 Spatio-temporal Visualisation

The time and magnitude of the clearing events are visualised in Figure 12. Figure 12a) shows the date of the first significant breakpoint between February 2000 and September 2009 for each clearing and potential re-clearing area as mapped in the SLATS clearing eras. The associated magnitude of change (in NDVI units) is provided in Figure 12 b) for comparison.

Figure 12 near here please.

5. Discussion

5.1 8 day STARFM data

As shown also by Schmidt et al. (2012) and Bhandari et al. (2012), the STARFM algorithm was found to produce good interpolated time-series (8 day frequency over a 12 year period) of the NDVI, with these representing the vegetation dynamics in this Australian environment. Spatial averages of Landsat, MODIS and STARFM data over homogeneous forest and grassland sites at 1.5 km x 1.5 km and 1 km x 1 km respectively were also similar (see Figure 5). However, high and low NDVI values in the time series were lower within the MODIS data compared to the Landsat and STARFM data. This was most evident in the grassland area and the forested site during the wet season of 2000/2001 and may be related to the spatial scale difference of the MODIS 500 m and the 30 m Landsat data as high and low values are often averaged when moderate spatial resolution data are fused with coarser resolution data.

The high repeat frequency data of the STARFM application provides new and important information on land use and vegetation dynamics that cannot be obtained from other sources. Whilst applied to a small study area in this case, there is the potential for application across larger areas including the state of Queensland (88 Landsat footprints). However, processing times and data storage may be limiting factors and reducing the temporal frequency to 16 day or monthly time-steps should be considered. Spatial interpolation methods (e.g., Pringle et al., 2009) also need to be considered to account for the SLC-off effect and prevent significant data gaps. Potential improvements to the prediction might result from the application of improved versions of the STARFM algorithm (Zhu et al., 2010; Fu et al., 2013). Whilst not considered in this study, other standardized vegetation indices derived from fractional cover estimates might also be used (Scarth, et al., 2010; Schmidt and Scarth, 2009).

5.2 Change detection

Across the ILCP, a number of PSUs were associated with stable vegetation, as identified by referencing time-series of LIDAR and aerial photography. Within these stable areas, the NDVI fluctuated largely in response to rainfall, with the upward trend from the mid 2000s onwards attributable to recovery from the intense drought of 2006. In these evergreen environments, the dry season component is often contributed by the overstorey component and so the NDVI within intact vegetation increase may reflect the processes of woody thickening. The recommendation is that trajectories from these stable sites be used as reference against which to assess the vegetation response in different ecosystems, bioregions or climate zones. This would allow, for example, investigations into management impacts on forest response and provide a reference dataset for ecosystem functionality that may be linked to biodiversity indicators or land cover dynamics (Bastin, et al. 2012; Caroll, et al. 2011).

Outside of the stable areas, a wide range of changes has occurred within the ILCP. These include the complete clearing of vegetation so that land can be used for agriculture, re-clearing of regrowth and partial clearing through selective logging (primarily of CP-). Changes induced by natural events were largely associated with fires (e.g., in 2003, 2010 and 2011 after wet years with sufficient understorey fuel accumulation). Other processes leading to loss of forest cover include the natural competition and succession of trees, although tree dieback was also associated with the periods of drought. Extensive areas of regrowth on land previously cleared or subject to fire were also observed. Much of the regrowth was dominated by one or several species (e.g., BGL, PBX). Such changes were often not detected by comparing annual satellite-derived maps of forest and non-forest, but the use of hyper-temporal actual and simulated Landsat sensor data provided an opportunity to identify specific events and/or processes relating to disturbance and regeneration. Seasonal minimum NDVI shows a close correspondence to annual FPC as shown by Schmidt, et al. (2012) and thus provides the best option for quantifying land cover transitions as the influence of ephemeral vegetation is reduced.

Whilst change is best detected when observed directly by the Landsat sensor, either just before or after the event, the STARFM products are beneficial. In particular, the integration of the high temporal resolution information from the MODIS with the finer spatial resolution Landsat imagery in a time-series allows a better description of the phenological changes that are occurring. Indeed, some changes can only be identified when the temporal context is given. The parameters of the BFAST algorithm can also be set to identify multiple change events

(Verbesselt et al., 2010), with the number, time and magnitude being of particular relevance for natural resource management. By also tracking the temporal signal, the regeneration of forests can be observed and rates determined with different time segments of the seasonal minima of the NDVI being useful for mapping different land cover transitions. The time-series data may be used to detect clearing and clearing of regrowth; and might assist in speeding up the compliance process and reduce uncertainties (Goulevitch, 2012).

Maps showing the time of the clearing event and the magnitude of the NDVI change are displayed in Figure 12.   All areas labelled as cleared in Figure 3d), including potential re-clearing sites, were investigated. A prior knowledge of clearing was used in this approach and BFAST allowed the most significant change event in the time-series to be detected. The primary clearing event could be identified with a high degree of accuracy but re-cleared areas were less able to be detected.

5.3 Validation

For validation of change, the full time-series of Landsat sensor data was used as ground-based data or aerial photographs for the clearing date were not available. The maximum length of time between any two Landsat data acquisition was 60 days. These intervals were intersected with the confidence intervals around the breakpoint estimates from BFAST.

SSUs were treated as independent observations. It could be argued that the analysis should be performed on a PSU basis to reduce the spatial dependency, but the sample appeared to be not large enough to derive statistically meaningful statements based on a summarised PSU basis.

State-space models which explicitly take the spatial context into account might overcome this, but are generally computationally quite expensive.

6. Conclusions

An 8-day interval time series of STARFM generated data based on 525 MODIS and 97 Landsat images was generated for a period of 12 years and with a time-interval of 8 days. The correlations between the MODIS and STARFM time series were 0.92 and 0.96 ($r2 = 0.84$ and 0.94) for a homogeneous forested and grassland area respectively. The correlations (r and r2) between Landsat and the closest simulated STARFM data were 0.99 in all cases. The hyper-temporal NDVI time series were suitable for detecting primary clearing events with 94 % accuracy within 40 days of a clearing event. The minimum NDVI within this time series was also used to track regrowing vegetation. For stable areas of vegetation, identified using temporal LIDAR data, the NDVI reflectance trajectories were variable and different in magnitude but trends were similar. The study highlighted the benefits of using STARFM generated data for observing and quantifying trends in vegetation dynamics with potential applications for land management and forest conservation.

Acknowledgements

The authors would like to thank the Queensland International Fellowship program who supported this work and the (anonymous) reviewers for their comments.

References

Asner, G.P., Knapp, D.E., Broadbent, E.N., Oliveira, P.J.C., Keller, M. & Silva, J.N. (2005) Selective logging in the Brazilian Amazon. Science, 310(5747): 480–482. DOI: 10.1126/science.1118051.

Armston, J.D., Denham, R.J., Danaher, T.J., Scarth, P.F. & Moffiet, T.N., (2009). Prediction and validation of foliage projective cover from Landsat-5 TM and Landsat-7 ETM+ Imagery. Journal of Applied Remote Sensing 3 (033540), doi: 10.1117/1.3216031.

Baumann, M., Kuemmerle, T., Elbakidze, M., Ozdogan, M., Radeloff, V.C., Keuler, N.S., et al., (2011). Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. Land Use Policy 28 (3), 552-562.

Bastin, G., Scarth, P., Chewings, V., Sparrow, A., Denham, R., Schmidt, M., O'Reagain, P., Shepherd, R., & Abbott, B. (2012). Separating grazing and rainfall effects at regional scale using remote sensing imagery: A dynamic reference-cover method. Remote Sensing of Environment, 121, 443-457.

Bhandari, S., Phinn, S.R. & Gill, T. (2012) Preparing Landsat image time series (LITS) for monitoring changes in vegetation phenology in Queensland, Australia, Remote Sensing, 2012, 4, 1856-1886; doi:10.3390/rs4061856.

Carroll, C., Waters, D.,Vardy, S., Silburn, M., Attard,S., Thorburn, P., Davis, A., Halpin, N., Schmidt, M., Wilson,B. & Clark, A. (2012). A Paddock to reef monitoring and modelling framework for the Great Barrier Reef: Paddock and catchment component. Marine Pollution Bulletin. 65, 136–149.

Danaher, T., Scarth, P., Armston, J., Collett, L., Kitchen, J. & Gillingham, S. (2010). Remote Sensing of Tree-Grass Systems – the Eastern Australian Woodlands, In: Ecosystem Function in Savannas: Measurement and Modeling at Landscape to Global Scales, Hill, M.J. and Hanan, N.P. (Eds.), Taylor and Francis, pp. 175-193.

Emelyanova, I.V, McVicar, T.M., van Neil, T.G. & van Dijk, A. (2013). Assessing the accuracy of blending Landsat–MODIS surface reflectances in two landscapes with contrasting spatial and temporal dynamics: A framework for algorithm selection. Remote Sensing of Environment 133:193-209. DOI: 10.1016/j.rse.2013.02.007

Gao, F., Masek, J., Schwaller, M. & Hall, F. (2006). On the blending of the Landsat and MODIS surface reflectance: Predicting daily Landsat surface reflectance. IEEE Transactions on Geoscience and Remote Sensing 44 (8), 2207-2218.

Flood, N., Danaher, T., Gill, T. & Gillingham, S. (2013). An Operational Scheme for Deriving Standardised Surface Reflectance from Landsat TM/ETM+ and SPOT HRG Imagery for Eastern Australia. Remote Sensing, 5(1), 83-109. doi:10.3390/rs5010083.

Fu, D., Chne, B. Wang, J, Zhu, X. & Hilker, T. (2013): An Improved Image Fusion Approach Based on Enhanced Spatial and Temporal the Adaptive Reflectance Fusion Model. Remote Sens. 2013, 5, 6346-6360; doi:10.3390/rs5126346

Goodwin, N. R., & Collett, L. J. (2014). Development of an automated method for mapping fire history captured in Landsat TM and ETM+ time series across Queensland, Australia. Remote Sensing of Environment, 148, 206–221.

Goulevitch, B. (2012). Ten Years of Using Earth Observation Data in Support of Queensland's Vegetation Management Framework, In: Evidence from Earth Observation Satellites, Purdy, R. and Leung, D. (Ed.), Brill, Leiden, The Netherlands.

Hilker, T., Wulder, M.A., Coops, N.C., Seitz, N., White, J.C., Gao, F., et al. (2009). Generation of dense time series synthetic Landsat data through data blending with MODIS using a spatial and temporal adaptive reflectance fusion model. Remote Sensing of Environment 113 (9), 1988-1999.

Hilker, T., Wulder, M.A., Coops, N.C., Linke, J., McDermid, G., Masek, J.G., Gao, F. & White, J.C. (2009). A new data fusion model for high resolution mapping of forest disturbance based on Landsat and MODIS. Remote Sensing of Environment, 113(8), 1613-1627.

Jönsson, P. & Eklundh, L. (2004). TIMESAT - A program for analyzing time seriesof satellite sensor data. Computers and Geosciences 30 (8), 833-845.

Kauth, R., & Thomas, G. (1976). The tasselled cap- A graphical description of the spectral-temporal development of agricultural crops as seen by Landsat. Proceedings of the Symposium on Machine Processing of Remotely Sensed Data, Purdue University of West Lafayette, Indiana, 1976, pp. 4B-41 to 4B-51.

Kennedy, R.E., Townsend, P.A., Gross, J.E., Cohen, W.B., Bolstad, P., Wang, Y.Q., et al. (2009). Remote sensing change detection tools for natural resource managers: Understanding concepts and tradeoffs in the design of landscape monitoring projects. Remote Sensing of Environment 113 (7), 1382-1396.

Lee, A.C. & Lucas, R.M. (2007). A LiDAR-derived canopy density model for tree stem and crown mapping in Australian forests. Remote Sensing of Environment 111 (4), 493-518.

Pringle, M.J., Schmidt, M. & Muir, J.S. (2009). Geostatistical interpolation of SLC-off Landsat ETM+ images. ISPRS Journal of Photogrammetry and Remote Sensing 64 (6), 654-664.

Roy, D.P., Ju, J., Lewis, P., Schaaf, C., Gao, F., Hansen, M., et al. (2008). Multi-temporal MODIS-Landsat data fusion for relative radiometric normalization, gap filling, and prediction of Landsat data. Remote Sensing of Environment 112 (6), 3112-3130.

Running, S.W. & Nemani, R.R. (1988). Relating seasonal patterns of the AVHRR vegetation index to simulated photosynthesis and transpiration of forests in different climates. Remote Sensing of Environment 24 (2), 347-367.

Scarth, P., Roeder, A. & Schmidt, M. (2010). Tracking grazing pressure and climate interaction - The role of Landsat fractional cover in time series analysis, Alice Springs, Australia ed. In: Proceedings of the 15th Australasian Remote Sensing and Photogrammetry Conference, September 2010.

Schmidt, M. & Scarth, P., 2009. Spectral mixture analysis for ground-cover mapping, In: Innovations in Remote Sensing and Photogrammetry, Jones, S. and Reinke, K. (Eds.), Springer Heidelberg, Dortrecht, London, New York, pp. 349-359.

Schmidt, M., Udelhoven, T., Gill, T. & Röder, A. (2012). Long term data fusion for a dense time series analysis with MODIS and Landsat imagery in an Australian Savanna. Journal of Applied Remote Sensing, 6 (063512), doi: 10.1117/1.JRS.6.063512.

Schöttker, B., Phinn, S. & Schmidt, M. (2010). How does the global MODIS FPAR product relate to regionally developed land cover and vegetation products in a semi-arid Australian Savanna? Journal of Applied Remote Sensing, 4 (43538), doi: 10.1117/1.3463721.

Tickle, P.K., Lee, A., Lucas, R.M., Austin, J. & Witte, C. (2006). Quantifying Australian forest floristics and structure using small footprint LiDAR and large scale aerial photography. Forest Ecology and Management 223 (1-3), 379-394.

Tucker, C.J. (1979). Red and Photographic Infrared Linear Combinations for Monitoring Vegetation, Remote Sensing of Environment, 8(2),127-150.

van der Werf, Morton, D.C., DeFries, R.S., Olivier, J.G.J., Kasibhatla, P.S., Jackson, R.B., et al. (2009). CO2 emissions from forest loss. Nature Geoscience, 2 (11), 737-738.

Verbesselt, J., Hyndman, R., Newnham, G. & Culvenor, D. (2010). Detecting trend and seasonal changes in satellite image time series. Remote Sensing of Environment 114 (1), 106-115.

Verstraete, M.M. & Pinty, B. (1996). Designing optimal spectral indexes for remote sensing applications. IEEE Transactions on Geoscience and Remote Sensing 34 (5), 1254-1265.

Walker, J.J., de Beurs, K.M., Wynne, R.H. & Gao, F. (2012). Evaluation of Landsat and MODIS data fusion products for analysis of dryland forest phenology. Remote Sensing of Environment 117 (0), 381-393.

Watts, J.D., Powell, S.L., Lawrence, R.L. & Hilker, T. (2011). Improved classification of conservation tillage adoption using high temporal and synthetic satellite imagery. Remote Sensing of Environment 115 (1), 66-75.

Wulder, M.A, Masek, J,G., Cohen, W.B., Loveland, T.R. &Woodcock,C.E. (2012): Opening the archive: How free data has enabled the science and monitoring promise of Landsat. Remote Sensing of Environment, 122, 2–10, DOI: 10.1016/j.rse.2012.01.010

Williams, R.J., Myers, B.A., Muller, W.J., Duff, G.A. & Eamus, D. (1997). Leaf phenology of woody species in a North Australian tropical savanna. Ecology 78 (8), 2542-2558.

Witt, G.B., Harrington, R.A. & Page, M.J. (2009). Is vegetation thickening occurring in Queenslands mulga lands? A 50-year aerial photographic analysis. Australian Journal of Botany 57 (7), 572-582.

Zhu, X., Chen, J., Gao, F., Chen, X. & Masek, J.G. (2010). An enhanced spatial and temporal adaptive reflectance fusion model for complex heterogeneous regions. Remote Sensing of Environment 114 (11), 2610-2623.

Zhu, Z. & Woodcock, C.E. (2012). Object-based cloud and cloud shadow detection in Landsat imagery. Remote Sensing of Environment 118 (0), 83-94.

Figure captions:

Figure 1: a) and b) The location of the Injune study area in Queensland, the dotted lines in c) indicate approximately the centre of the Landsat ETM+ swath unaffected by the SLC-off effect. d) the arrangement of the Primary Photo Plot (PPP), Primary Sampling Units (PSU) and Secondary Sampling Units (SSU) and the layout of the sampling grid.

Figure 2: The distribution of Landsat TM (black) and ETM+ (grey) images available for the ILCP area and used as input to the STARFM simulations.

Figure 3: July, 7 2011 data (red band reflectance) of the ILCP research area: a) Landsat TM; b) MODIS, July , 12 2011; and c) STARFM simulated image also July, 7 2011. d) The Statewide Land Cover and TreeS (SLATS) map of clearing by year. The PSU grid is overlaid in a), in b) are two homogeneous forest (R1) and grassland sites (R2) marked.

Figure 4: Scatterplots of band 3 and 4 for Landsat 5 TM and STRAFM image of the same date: June 1, 2004. The Landsat image was withheld from the utilisation in the STARFM predictions. The dotted red line represents the 1:1 line, the data points are a 10% random sample across the study area.

Figure 5: MODIS, Landsat and STARFM NDVI time series data for homogeneous regions a) a 1.5 km x 1.5 km forested area (R1; see Figure 3) and b) a 1 km x 1 km grassland area (R2; see Figure 3). The vertical dotted lines indicate intervals were the phonological signal would differ with Landsat imagery alone.

Figure 6: Residual plot for R1 a) and R2 b) of all Landsat (TM/ETM+) NDVI data and the closest simulated STARFM NDVI image. The dotted line represents one standard deviation.

Figure 7: The processes of clearing and regrowth observed by comparing LiDAR height data acquired in 2000 and 2009 (for PSU 108) both a) in plan view and b) in profile. The dashed white line in the 2009 image plots the transect of the profile data.

Figure 8: a) Time-series of the NDVI for stable vegetation (determined through interpretation of high resolution airborne sensor datasets) showing the mean and standard deviation for the period 2000-2012. A general increase with monthly rainfall (mm) is evident. b) Anomalies of the NDVI from the mean trajectory of stable vegetation as a function of different forest types with different species dominating (7 examples). The black line represents two standard deviations from the mean.

Figure 9: a) NDVI time series for stable vegetation and for two areas (PSUs 108 and 68), which were originally occupied by C. glaucophylla, E. melanaphloia and other Eucalpytus species (CP-SLIEUS) and by E. populnea (PBX) respectively, but then cleared in 2000 and 2002. Trends in the difference between the mean NDVI for all vegetation types combined and for the two disturbed areas are shown for a) PSU 108 and b) PSU 68. The break points in the time series indicate the clearing event and the magnitude of change in the NDVI, the confidence interval is indicated in red.

Figure 10: Time series of the seasonal minimum of NDVI for a stable forest (PSU 67), a stable non-forest (PSU 141) and the two different regrowth areas (PSU 68 and 108). Note that PSUs 141 and 68 were cleared of forest prior to 2000.

Figure 11: Comparison of estimated (BFAST breakpoint) intervals (blue) and reference clearing internals (cyan) for a) clearing and b) re-clearing. The breakpoint confidence intervals were computed by BFAST, and the reference intervals were established with all available Landsat imagery. The first date in the reference interval is plotted as base value (zero) on the y-axis. The dashed red line shows a 40 day interval.

Figure 12: a) the clearing date determined using the BFAST breakpoint detection and b) the magnitude of NDVI change at the time of clearing for all clearing and re-clearing areas within the study region.